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## Cognitive Simulation Driven Domestic Heating Energy Management

Dilhan J. Thilakarathne, Jan Treur\*

*Agent Systems Research Group, VU University Amsterdam, The Netherlands*

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### Abstract

Energy management for domestic heating is a non trivial research challenge, especially given the dynamics associated to indoor and outdoor air temperatures, required comfortable temperature set points over time, parameters of the heating source and system, and energy loss rate and capacity of a house. In addition to all these factors, human influence or interaction is also a key aspect in this complex system. It is difficult and very costly to conduct experiments of this nature to scrutinize the dynamics and optimal efficiency of the system under all circumstances and constraints. This paper focuses on a domestic heating energy management system using an air to water heat pump and uses a pre-developed mathematical model for its performance. This mathematical model is integrated within a computational dynamic cognitive model which was developed based on neurocognitive evidence. An approach like this can be used as an experimental workbench for complex scenarios.

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**Keywords:** Heating energy management; Cognitive modeling; Mathematical model; Heat pump; Short term and long term goals

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### 1. Introduction

Energy is an important ingredient for the development of a country and adequate energy management is a vital aspect for a sustainable development. In many countries most of the energy usage goes to domestic heating and cooling [1, 2]. The amount of energy that can be saved by properly managing the energy usage of a house may not be felt as very significant, but in a global context it surely may provide a significant contribution to a better environment in the future. It has been observed that a major portion of energy used for domestic heating and cooling

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\* Corresponding author. Tel.: +3-120-598-7763; fax: +3-120-598-7653.

E-mail address: [jtreur@vu.nl](mailto:jtreur@vu.nl)

is needlessly wasted [2]. Therefore, many researchers focus on how to reduce domestic energy usage, specifically for heating related energy usage. The research reported here addresses different aspects of energy saving, among others making use of predicting variations in outside temperature, characteristics of a house, user preferences, improved devices, and usage of renewable energy sources. This paper mainly focuses on domestic heating management through an air to water heat pump together with relevant human cognition. For performance of an air to water heat pump a mathematical model was already developed [3]. This model describes the performance of an air to water heat pump, over time, in relation to variation both for indoor and outdoor temperatures and characteristics of a house. This model has been validated with realistic simulations and partly with empirical data [3,4].

Due to the developments in brain imaging and recording techniques, the insight in human brain processes is growing rapidly. This contributes to an improved quality of relevant data and knowledge, and to the development of new methods to explore this most complex system within human anatomy through different dimensions. Based on findings from Cognitive Neuroscience, a dynamic computational model was developed for action selection taking into account situation awareness [5]. This model includes a number of relevant cognitive states: performative desires, subjective desires, feeling, action preparation, ownership, attention, intention, and awareness. It models the interplay between conscious and unconscious processes. Behavior of inhabitants in a house has a strong impact on the energy consumption and it is an important factor for energy waste reduction, especially in a dynamic context [6].

This paper combines the mathematical model that was developed for analysis of smart daily energy management for an air to water heat pump with the cognitive model for situation awareness. It is a common problem in energy related research that practical experiments cost a lot in effort and money. Furthermore, when it is required to integrate human cognition also into the experiment it is much harder. Having this type of research contributes to facilitate a sophisticated working environment to simulate complex situations including behaviour of both technical systems and humans. This paper focuses on a single house with a human's desires and intentions for selecting night indoor temperature. An inhabitant has desires on a comfort level required at night, strong desires to save money, and has to balance between comfort level and money (or energy) saving.

## 2. A mathematical model for heating by a heat pump and a cognitive model for action selection

This paper integrates two models that have been developed earlier. The first explains a mathematical model for the domestic energy usage by using an air-to-water heat pump. Due to space limitations only a brief description of this model will be presented in the current paper; more details can be found in [3]. The model calculates the energy used to heat a house over time according to a particular heating program. The second model covers cognitive processes behind action selection taking into account situation awareness; it has been applied to analyse the role of situation awareness in the aviation domain in [5]. This model addresses the interplay of a bottom-up and a top-down process and in particular how they interact with each other in order to cognitively drive a given situation to an adequate action.

### 2.1. Mathematical model for the domestic energy usage by an air-to-water heat pump

For a mathematical model of domestic energy usage by an air to water heat pump there are various dynamic factors to be considered. Among them one is the dynamics of outdoor air temperature. This also further can be divided into two parts daytime and nighttime outdoor air temperature. The outdoor air temperature typically shows a 24h periodic behavior (e.g., [7, 8]) and therefore also the energy usage to maintain a constant indoor temperature will vary over the time of a day. Sine-exponential and sinusoidal models are the most common analytical models used for this purpose. They calculate the pattern of outdoor temperatures over a day (and night) based on four parameters: sunrise time ( $t_{\text{sunrise}}$ ) and sunset time ( $t_{\text{sunset}}$ ), and maximum ( $T_{\text{max}}$ ) and minimum ( $T_{\text{min}}$ ) temperature values over the day [7]. Note that these are parameters for one given day, but they themselves are in fact variables at a time scale over a year, as they differ from day to day.

Equation (1) below presents the daytime outdoor temperature variation  $\text{dot}(t)$  and equation (2) presents the nighttime variation  $\text{not}(t)$ . The values for the time parameters and variables are relative to midnight. Here in the evening (before midnight)  $T_{\text{min}}$  refers to the minimum temperature ahead in time and in the early morning (after midnight) it is of the day itself; similarly in the early morning (after midnight)  $T_{\text{sunset}}$  refers to the temperature at

sunset of the previous day, but in the evening (before midnight) it refers to the temperature at sunset on the day itself.

$$\text{dot}(t) = b + a * \sin\left(\left(t - 15 + \frac{t_{\text{sunset}} - t_{\text{sunrise}}}{2}\right)\left(\frac{\pi}{t_{\text{sunset}} - t_{\text{sunrise}}}\right)\right) \quad (1)$$

where  $a = \left(T_{\text{max}} - T_{\text{min}} / \left(1 - \sin\left((t_{\text{sunrise}} - 9)\frac{\pi}{12}\right)\right)\right)$  and  $b = (T_{\text{max}} - a)$

$$\text{not}(t) = (T_{\text{min}} - d) + (T_{\text{sunset}} - T_{\text{min}} + d)e^{-\alpha(t - t_{\text{sunset}})} \quad (2)$$

Another important element for the heating model is the notion of degree days ( $dd$ ). This concept  $dd$  has been introduced to approximate the analysis of energy consumption and energy performance of a building based on historical data (e.g., [9]). The number of degree-days is defined as the summation of individual deviations between the outdoor temperature  $T_{od}$  and a given indoor temperature  $T_{id}$  in each time step for a time interval from  $t1$  to  $t2$ . This can be expressed mathematically as:

$$dd(t1, t2) = \int_{t1}^{t2} (T_{id} - T_{od}(t))dt \quad \text{when } T_{id} > T_{od}(t) \text{ for all } t \text{ with } t1 \leq t \leq t2 \quad (3)$$

The next important process is natural indoor cooling down process when the heating system is off (where outdoor temperature is lower). The rate of change of the temperature of an object is proportional to the temperature difference between it and the ambient temperature [10]. When the ambient temperature is not a constant, modeling the indoor temperature under a cooling down process is a bit challenging. To approximate the time taken to cool down overnight from a given indoor temperature to another temperature early in the morning, it is crucial to know at each point in time the rate of change of the indoor temperature, thus obtaining a differential equation for  $T_{id}(t)$  which can be solved analytically or numerically. The following section adopts Newton's law of cooling down for this; equation (4) presents the decay of indoor temperature under natural cooling down with varying ambient temperature. Here  $k$  is the heat transfer coefficient; it consists with energy loss per degree day  $\varepsilon$  and the energy needed per degree increase of temperature (capacity  $C$ ). The detail steps of deriving the equation (4) can be found in [3].

$$T_{id}(t) = P + \left(f(t_1) - p + \frac{kQe^{\alpha t_{\text{sunset}}}}{\alpha - k}\right)e^{-k(t - t_1)} - \left(\frac{kQe^{\alpha t_{\text{sunset}}}}{\alpha - k}\right)e^{-\alpha(t - t_1)} \quad (4)$$

where  $k = \frac{\varepsilon}{24C}$ ,  $P = (T_{\text{min}} - d)$ ,  $Q = (T_{\text{sunset}} - T_{\text{min}} + d)$ ,  $t_1$  is the starting time of the cooling down process,

$$f(t) = -\frac{A}{B} + \varphi e^{Bt} - \left(\frac{D}{\alpha + B}\right)e^{-\alpha t}, \varphi = \left(f(t_1) + \frac{A}{B} + \left(\frac{D}{\alpha + B}\right)e^{-\alpha t_1}\right)e^{-Bt_1}, A = kP, B = -k, \text{ and } D = kQe^{\alpha(t_1 + t_{\text{sunset}})}$$

To estimate from this the time taken in the cooling down process for a given loss of temperature  $\Delta T$  it is not possible to find the roots by directly solving the non-linear exponential equation in  $t$  in (4). However, an adequate approach for this is to use a standard numerical method which is able to approximate roots with a sufficient accuracy. Newton's method [11] is a good choice for this due to its simplicity and good speed.

Finally it is important to understand the performance of the heat pump. The performance of a heat pump is indicated by its Seasonal Performance Factor  $SPF$  in equation (5): the ratio of the heat delivered by the heat pump (energy output:  $eo$ ) and the electrical energy supplied to it (energy input:  $ei$ ). Being a dynamic property over the outdoor temperature, to approximate its value in a linear manner, equation (6) (adopted from [9, 16]) can be used.

$$SPF = \frac{\text{energy output}}{\text{energy input}} = \frac{eo}{ei} \quad (5)$$

$$SPF(T_{od}) = 7.5 - 0.1(T_w - T_{od}) \quad (6)$$

where  $T_w$  is the heating system water temperature and  $T_{od}$  is the outdoor temperature

The energy demand ( $ed$ ) for heating over time is an essential factor in the analysis of energy usage. It mainly concerns (1) maintaining a particular indoor temperature (thermal comfort) over a certain time period given the

natural loss of heat, and (2) increasing the indoor temperature from a low value (for example, overnight) to a higher value wanted over some time period. The temperature maintenance energy demand (*tmed*) depends on the energy loss for a given pair of indoor and outdoor temperatures (where outdoor temperature < indoor temperature): it indicates the amount of energy through the heating system to compensate for this loss and thus to maintain the given indoor temperature. The degree-days concept expresses this energy loss [6]; the energy loss per degree-day is assumed to be  $\varepsilon$ ; this is different for each house/building and depends on the isolation of the border between indoor and outdoor with walls, windows, floor, roof, ventilation, for example. For a given time interval, the value of *tmed* can be expressed as in equation (7). Furthermore, temperature increase energy demand (*tied*) depends on the heat energetical capacity  $C$  of the house: this indicates how much energy is needed to raise the temperature by 1 degree. Therefore *tied* is proportional to the temperature difference  $\Delta T_{id}$  made and relates to the notion of capacity  $C$  of the house as in the equation (8). Finally the total energy demand can be expressed as in equation (9).

$$tmeu(t_1, t_2) = \int_{t_1}^{t_2} \frac{\varepsilon}{24} (T_{id} - T_{od}(t)) dt \quad (\text{assuming } T_{id} > T_{od}(t)) \quad (7)$$

$$tied = C \Delta T_{id} \quad (8)$$

$$ed = tmed + tied \quad (9)$$

For a small time interval with length  $\Delta t$  the energy usage *eu* is proportional to the energy demand and relates to the seasonal performance factor *SPF* of the heat pump as expressed in equations (10).

$$eu(t, t + \Delta t) = \frac{ed(t, t + \Delta t)}{SPF(T_{od}(t))} \quad (10)$$

## 2.2. Computational dynamic cognitive model for human action selection

Human action selection is a complex process and the exact mechanisms of it are still being explored. Nevertheless, due to the developments in brain imaging and recording techniques much knowledge about this has been developed. This knowledge provides means to design and implement models for human action selection in more accurately. Details of neurocognitive evidence behind human action formation will not be included in the current paper but can be found separately in [5,12]. Fig. 1 presents the cognitive model for action selection and Table 1 summarizes the abbreviations used. The model takes inputs from two types of world states:  $WS(s_k)$  and  $WS(b_i)$ ; here  $s$  is a stimulus (that can be either external or internal to the agent) that may lead to an action execution, and  $b_i$  represents the effects of the execution of an action  $a_i$ . The world state  $WS(s_k)$  leads to a sensor state  $SS(s_k)$  as input, and subsequently to a sensory representation state  $SR(s_k)$ . Moreover, the model includes both conscious and unconscious aspects. The states:  $SR(s_k)$ ,  $SR(b_i)$ ,  $PD(b_i)$ ,  $PA(a_i)$ ,  $F(b_i)$ ,  $Per(b_i, s_k)$ ,  $PO(a_i, b_i)$ , and  $RO(a_i, b_i)$ ; are considered to be unconscious and contributing to bottom-up processes, whereas the states:  $SD(b_i)$ ,  $Att(b_i, s_k)$ ,  $CInt(b_i, s_k)$ ,  $PAwr(a_i, b_i, s_k)$ , and  $RAwr(a_i, b_i, s_k)$ ; represent more conscious influences, contributing to top-down processes. The bottom-up cognitive processes have been mapped to unconscious action formation, whereas top-down processes have been related to the conscious action formation [13–16]; it seems that the action selection process initiates from unconscious phenomena, and that later the conscious experience of this action selection is developed. The unconscious neural activations in the brain seem to be a result of habitual tasks, through the effects of prior learning, which can be automatically activated when a relevant stimulus is perceived [17]. Nevertheless, conscious awareness of action selection also plays an important role and the influence of predictive and inferential processes of action execution has been highlighted by Haggard and co-workers, providing a working mechanism for this process [13].

The unconscious bottom-up process of action selection is modeled by combining Damasio's as if body loop [18] and James's body loop [19]. The as if body loop presented through:  $PA(a_i) \rightarrow SR(b_i) \rightarrow F(b_i)$  and body loop is presented through  $PA(a_i) \rightarrow EA(a_i) \rightarrow WS(b_i) \rightarrow SS(b_i) \rightarrow SR(b_i) \rightarrow F(b_i)$ . According to Damasio, the cognitive process of action selection is based on an internal simulation process prior to the execution of an action. Effects of each relevant action option  $PA(a_i)$  (a stimulus  $s$  will have many options  $i=1..n$ ) are evaluated (without actually executing them) by comparing the feeling-related valuations associated to their individual effects. When actions are assumed mutually exclusive, each preparation state  $PA(a_i)$  for action option  $a_i$  suppresses preparation of all its

complementary options  $PA(a_j)$  with  $j \neq i$  (see Fig. 1), and therefore by a kind of winner-takes-all principle, naturally the option that has the highest valued effect felt by the agent will execute through the body loop.

This process is further strengthened by embedding performative desires for  $b_i$  and perception states for  $s_k$  on  $b_i$ . The state  $PD(b_i)$  facilitates short-term interests/goals that influence either selecting or rejecting an action due to its satisfactory or less satisfactory valuation. Therefore, through this state, the agent has the ability to strengthen the current action selection based on its desires (through this, also some bias can be injected into the process). In parallel to the action preparation process, the perception state  $Per(b_i, s_k)$  also develops based on the salient features of the stimulus  $s_k$ ; this will strengthen the bottom-up process which leads to even further strengthening of the action preparation process. Furthermore; by having a suppressive link from the  $Per(b_i, s_k)$  state to itself (see Fig. 1), the competition among perceptual entities is represented [20]. While the agent is passively (unconsciously) performing an action selection, the agent starts to activate bottom-up attention (this is represented by the link from  $F(b_i)$  to  $Att(b_i, s_k)$ ). The main functionality of the bottom-up attention is to pass current information into higher order cognitive states. Due to this bottom-up attention, the agent will activate its subjective desires of  $b_i$ ,

which in turn leads to a conscious intention of stimulus  $s_k$  and effect  $b_i$ , and subsequently back to the attention state again. This cyclic process represents the transformation from bottom-up to top-down. Intention is considered to trigger goal directed preparation (see [12]) and therefore this model includes an effect from the conscious intention state  $CInt(b_i, s_k)$  to the preparation state  $PA(a_i)$ . This link strengthens the option of action  $a_i$  but suppresses its complementary options for all  $PA(a_j)$  with  $j \neq i$ . This is also a part of the top-down process.

Once the attention (and its subjective aspects) has been developed, it injects conscious biases (through the top-down attention) into the action preparation and perception states. This is represented through the links from  $Att(b_i, s_k)$  to  $PA(a_i)$  and  $Per(b_i, s_k)$ , and these links (purple dotted arrows) play a special role: while activating the matching option (i.e., the  $i^{th}$

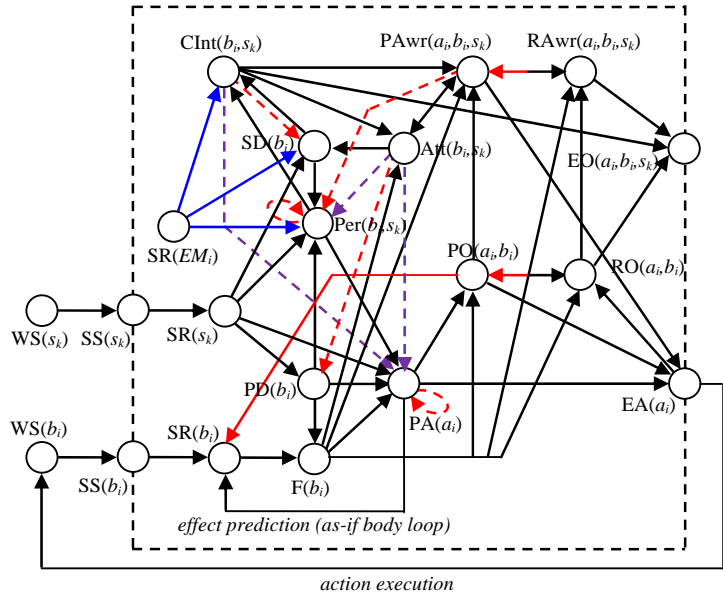


Fig. 1: Overview of the computational cognitive agent model. Here each solid black arrow represents a direct activation to state B from state A, each solid red arrow represents a direct suppression to state B from state A, each dashed red arrow represents a suppression to all the complements of ' $i^{th}$ ' state on  $B_i$  from state  $A_i$  (where ' $i$ ' presents an instance of a particular state), and each dashed purple arrow represent a direct activation to state  $B_i$  from state  $A_i$  while suppressing all the complements of ' $i^{th}$ ' state on  $B_i$  from state  $A_i$ .

Table 1: Nomenclature for Fig. 1

WS( $W$ )	world state $W$ ( $W$ can be either stimulus $s$ , or effect $b$ )
SS( $W$ )	sensor state for $W$
SR( $W$ )	sensory representation of $W$
PD( $b_i$ )	performative desires for $b_i$
SD( $b_i$ )	subjective desires for $b_i$
PA( $a_i$ )	preparation for action $a_i$
Per( $b_i, s_k$ )	perception state for the effect of $s_k$ on $b_i$
F( $b_i$ )	feeling for action $a_i$ and its effects $b_i$
PO( $a_i, b_i$ )	prior ownership state for action $a_i$ with $b_i$
Att( $b_i, s_k$ )	attention state for for the effect of $s_k$ on $b_i$
CInt( $b_i, s_k$ )	conscious intention state for $s_k$ on $b_i$
PAwr( $a_i, b_i, s_k$ )	prior-awareness state for action $a_i$ with $b_i$ and $s_k$
EA( $a_i$ )	execution of action $a_i$
RO( $a_i, b_i$ )	retrospective ownership state for action $a_i$ with $b_i$
RAwr( $a_i, b_i, s_k$ )	retrospective-awareness state for action $a_i$ with $b_i$ and $s_k$
EO( $a_i, b_i, s_k$ )	communication of ownership and awareness of $a_i$ with $b_i$ and $s_k$
SR(EM $_i$ )	sensory representation of energy model

option) they suppress all complements of the  $i^{\text{th}}$  option. The suppressive effects of this phenomenon are in line with the voluntary inhibition process (i.e., intentional suppression of an irrelevant response, stimulus, or memory); see [21]. This emphasizes the conscious influence on action formation, and therefore attention will quickly enable the agent's concentration, which may shorten the time required for action selection. More importantly, particular to the perceptual load, this will strengthen the current perception even further, and due to strong subjective feelings the agent may not be able to shift its attention easily. Together with these processes, the agent will develop a state of ownership, which mainly determines to what extent an agent attributes an action to himself or to another agent. Also, the agent will develop an awareness state of action  $a_i$  that is related to effect  $b_i$  and stimulus  $s_k$ . According to Haggard ([13,15]), there may be an influence from awareness states to action selection; therefore, this model includes a link from prior-awareness state  $\text{PAwr}(a_i, b_i, s_k)$  to the action execution state  $\text{EA}(a_i)$ . The agent will execute the selected action  $a_i$  and then this action will have an effect in the environment (through world state  $\text{WS}(b_i)$ ), and be sensed again, through the body loop. Once an action is executed, this model also considers the retrospective aspects that Haggard and co-works pointed out [13,22]. Finally, the agent has the ability to communicate the process through state  $\text{EO}(a_i, b_i, s_k)$ .

### 3. Cognitive driven domestic heating energy management

The main scope of this paper is to include cognitive aspects into the energy related decision making. As presented in Section 2, a mathematical model was developed earlier that can be used to calculate realistic results for energy usage of a house which uses air to water heat pump, and also a generic cognitive model was also developed earlier that mimics a detailed explanation of human action selection. In this section these two models will be combined resulting in an integrated model that will be able to simulate heating related energy management of a house together with cognitive elements. Mainly the cognitive model that was developed (see Fig. 1) is used as it is and mathematical energy model is embedded into it. Through this it is possible to keep required knowledge for the mathematical model in Section 2.1. The cognitive model accepts external information through the world state  $\text{WS}(s_k)$  and this is also used as the initiation of the process. Having this external input, it triggers the agent to select a set point for house indoor temperature. The main challenge in this situation is to decide which set point to be selected and how to perform that as close as possible to human cognition involved in action selection. In a real situation, a human may utilize his or her desires on comfort level, perception on energy related savings, and intentions to save money or energy. An agent can prepare for many possible options through multiple action preparation states  $\text{PA}(a_i)$ . For example, this can be interpreted as selecting set point value to  $18^\circ\text{C}$  ( $\text{PA}(a_1)$ ),  $16^\circ\text{C}$  ( $\text{PA}(a_2)$ ), or  $14^\circ\text{C}$  ( $\text{PA}(a_3)$ ). Before actually executing any option, the agent internally simulates the effects of these prepared options individually through the as if body loop. By comparing the feeling-related valuations associated to their individual effects that contribute to select the winning option: the option that has the strongest positive feeling will be the winning option to execute. To facilitate this it is required to have different weight values for the prediction connection from  $\text{PA}(a_i)$  to  $\text{SR}(b_i)$ . Having a strong link contributes to a strong feeling whereas having a weak link contributes to a poor feeling. In this model there are two types of connection links available: activation and suppressive. Activation links hold positive weight values (max value is +1 and the minimum is 0) and a suppressive link holds a negative weight value (max value is 0 and the minimum is -1). The complete information of the chosen weight values in Fig. 1 is presented in Table 2; the challenge in here is to select appropriate realistic values for them.

Through the as if body loop, by having different values for the links from  $\text{PA}(a_i)$  to  $\text{SR}(b_i)$  the agent develops different feelings about the options. Having significant differences between these values naturally leads to selection of the candidate with the strongest weight value. This can be considered as a habitual situation, in which user has executed the same decision many times and that has been hard coded by a very strong strength for that link (a form of neural plasticity). To eliminate such a bias effect it is made sure that the differences between weight values for the three options in the links from  $\text{PA}(a_i)$  to  $\text{SR}(b_i)$  are not significant (the selected difference is 0.1). Having such a situation now it is difficult for the agent to select its option and further cognitive aspects needs to be considered. For this purpose performative desires states  $\text{PD}(b_i)$  are used. These states facilitate short-term interests/goals that influence either selecting or rejecting an action due to its satisfactory or less satisfactory valuation (for more information see [23]). This can be used to express a human's expectation/desires on comfort level. If someone is more serious about its comfort level, it is natural to bias set points towards high temperature (considering a heating



situation). Performative desire states  $PD(b_i)$  directly affect feeling and action preparation states. Therefore, having a strong desire on comfort level will inject more bias to higher temperature set point values. This contributes to select an option easily through a strong predictive feeling and as the human is mainly (or partly) in unconscious mode or in a habitual mode this should quickly lead to action selection.

In parallel to the above process a perception state  $Per(b_i, s_k)$  also plays a key role. Having a strong perception leads to select an action quickly and contributes to strong emotions (for more details about the effects of perception on cognitive process see [5,24]). It is possible to easily develop a wrong or bias perception immediately from the input stimuli. Having a strong bias perception, may quickly lead to selection of a wrong option and the agent may be unable to correct this. This is considered to be the most frequent problem for poor situation awareness [25,26]. This model also explains the effects of bias perception, and specifically it has effects on the action preparation states  $PA(a_i)$  and conscious intention states  $CInt(b_i, s_k)$ . Therefore, having a strong perception injects strong influence on action preparation and leads to strengthening of the feeling through the as if body loop. The agent develops perceptions based on the results of the energy model. It is a well known fact that the energy cost that we save for heating by reducing the set point for one or a few degrees is not huge. If the agent has a biased perception, he or she will calculate the energy that will be saved by setting those set points and if the savings are not attractive, a strong perception on the highest set point value will be developed.

The effects and processes discussed above are mainly contributing to the unconscious or habitual form of action selection. Nevertheless, conscious aspects are also very important and especially if the human is expecting something contradicting with his/her comfort, this is a vital part. As highlighted in Section 2.2, this model includes

Table 2: Overview of the connections and their weights. Here the red colour  $\omega_k$  indicates negative weights

from states	to state	weights	LP
WS( $s_k$ )	SS( $s_k$ )	$\omega_1$	LP1
SS( $s_k$ )	SR( $s_k$ )	$\omega_2$	LP2
SR( $s_k$ ), Att'( $b_i, s_k$ )	PD( $b_i$ )	$\omega_3, \omega_4$	LP3
SR( $s_k$ ), PD( $b_i$ ), F( $b_i$ ), Per( $b_i, s_k$ ), CInt( $b_i, s_k$ ), CInt'( $b_i, s_k$ ), Att( $b_i, s_k$ ), Att'( $b_i, s_k$ ), PA( $a_i$ ) ( $j \neq i$ )	PA( $a_i$ )	$\omega_5, \omega_6, \omega_7,$ $\omega_8, \omega_9, \omega_{10},$ $\omega_{11}, \omega_{12}, \omega_{13}$	LP4
SR( $s_k$ ), PD( $b_i$ ), SD( $b_i$ ), Att( $b_i, s_k$ ), Att'( $b_i, s_k$ ), PAwr'( $a_i, b_i, s_k$ ), Per'( $b_i, s_k$ ), SR(EM <sub>i</sub> )	Per( $b_i, s_k$ )	$\omega_{14}, \omega_{15},$ $\omega_{16}, \omega_{17},$ $\omega_{18}, \omega_{19},$ $\omega_{20}, \omega_{em1}$	LP5
PA( $a_i$ ), SS( $b_i$ ), PO( $a_i, b_i$ )	SR( $b_i$ )	$\omega_{21}, \omega_{22}, \omega_{23}$	LP6
SR( $b_i$ ), PD( $b_i$ )	F( $b_i$ )	$\omega_{24}, \omega_{25}$	LP7
F( $b_i$ ), CInt( $b_i, s_k$ ), PAwr( $a_i, b_i, s_k$ )	Att( $b_i, s_k$ )	$\omega_{26}, \omega_{27}, \omega_{28}$	LP8
SR( $s_k$ ), Att( $b_i, s_k$ ), CInt'( $b_i, s_k$ ), SR(EM <sub>i</sub> )	SD( $b_i$ )	$\omega_{29}, \omega_{30},$ $\omega_{31}, \omega_{em2}$	LP9
Per( $b_i, s_k$ ), SD( $b_i$ ), SR(EM <sub>i</sub> )	CInt( $b_i, s_k$ )	$\omega_{32}, \omega_{33},$ $\omega_{em3}$	LP10
F( $b_i$ ), PA( $a_i$ ), RO( $a_i, b_i$ )	PO( $a_i, b_i$ )	$\omega_{34}, \omega_{35}, \omega_{36}$	LP11
PO( $a_i, b_i$ ), F( $b_i$ ), Att( $b_i, s_k$ ), CInt( $b_i, s_k$ ), RAWr( $a_i, b_i, s_k$ )	PAwr( $a_i, b_i, s_k$ )	$\omega_{37}, \omega_{38},$ $\omega_{39}, \omega_{40}, \omega_{41}$	LP12
PA( $a_i$ ), PO( $a_i, b_i$ ), PAwr( $a_i, b_i, s_k$ )	EA( $a_i$ )	$\omega_{42}, \omega_{43}, \omega_{44}$	LP13
EA( $a_i$ )	WS( $b_i$ )	$\omega_{45}$	LP14
WS( $b_i$ )	SS( $b_i$ )	$\omega_{46}$	LP15
EA( $a_i$ ), F( $b_i$ ), PO( $a_i, b_i$ )	RO( $a_i, b_i$ )	$\omega_{47}, \omega_{48}, \omega_{49}$	LP16
RO( $a_i, b_i$ ), F( $b_i$ ), PAwr( $a_i, b_i, s_k$ )	RAWr( $a_i, b_i, s_k$ )	$\omega_{50}, \omega_{51}, \omega_{52}$	LP17
RO( $a_i, b_i$ ), CInt( $b_i, s_k$ ), RAWr( $a_i, b_i, s_k$ )	EO( $a_i, b_i, s_k$ )	$\omega_{53}, \omega_{54}, \omega_{55}$	LP18

both unconscious and conscious processes. The initiation of the process is always as explained in above paragraphs. Once the agent developed predictive feeling about each option, that will lead to activation of the agent's attention (for detail cognitive basis of this see [5,12]). This is referred to as bottom-up attention and through this the agent starts to get more attention on what is happening unconsciously so far. Having developed some attention, this will further affect subjective desires for  $b_i$ . This is the state which represents long term goals of the user. The activation level of the subjective desire states depends on the results provided by the mathematical model. Due to triggering the mathematical model in here, now it is able to predict the energy required for individual situations/options. By having different energy needs for different set points, now the agent can decide which is the most economical (assuming the subjective desires to save money and energy). Therefore, the set point which is having the lowest energy demand should be highly motivated in this regard. As a result of that, the state SD( $b_i$ ) (for the 14°C option) strongly affects the conscious intention state for  $s_k$  on  $b_i$ . Therefore, for the lowest energy demand CInt( $b_i, s_k$ ) should be high and for the highest energy demand this should be relatively low. Having this feature now the state of CInt( $b_i, s_k$ ) becomes strong only if the energy used is minimum. Therefore, the agent naturally develops a strong intention to select that option

while other options are having a weak intention. There is a cyclic process among  $Att(b_i, s_k)$  to  $SD(b_i)$  to  $CInt(b_i, s_k)$ . Through this process it is natural that over time the agent experiences strong attention and intention on the option that minimizes the energy usage (together with the subjective desire of saving energy and money). Having this strong attention, now a new effect called top-down attention activates. Top-down attention involves a link from  $Att(b_i, s_k)$  to  $PA(a_i)$ . This is a very strong positive link and injects strong bias on action preparation consciously. Furthermore while attention for a particular option is strengthening its action preparation suppresses the preparations  $PA(a_j)$  for all the complements of that option (those with  $j \neq i$ ). Due to this, when a strong attention developed for an option, it will dominate the action selection process and other options will be diluted over time. This can be used to demonstrate the interplay between conscious and unconscious processes. Furthermore, in line with these processes, the agent develops a prior awareness state. This state also affects attention and also through this attention gets stronger. Finally, the state  $PAwr(a_i, b_i, s_k)$  affects action execution also, and this contributes to reduce the execution time under the conscious mode (conscious mode is relatively slow when compared with pure unconscious mode).

These processes will lead the agent to select an option and execute it through the state  $EA(a_i)$ . Once the action is executed the feelings of the actual action will be combined with the predicted feeling. Nevertheless, these retrospective effects are out of the scope of the current work; more detailed information on these processes can be found on [27]. These retrospective effects are very useful for learning and corrections if there is a mismatch between what is predicted and what is observed once the action is executed (see [5]).

### 3.1. Model Compilation as a Dynamic System

The above mentioned approach has been compiled into an executable model. For this a dynamical systems perspective is used, as explained in [28]. Each connection between states in Fig. 1 (the ones specified in Table 2) has been given a weight value (where  $\omega_{ji}$  represents the weight of the connection from state  $j$  to  $i$ ) that varies between 1 and -1 as indicated in Table 2. Weight values are non negative in general, except if they represent a suppressive (or inhibiting) link (see caption of Fig. 1). In addition to the link weights, each state includes an additional parameter called speed factor  $\gamma_i$ , indicating the speed by which the activation level of the state 'i' is updated upon receiving input from other states. Two different speed factor values are used, namely fast and slow values: fast values are used for internal states and slow values for external states (i.e., for  $WS(W)$ ,  $SS(W)$ ,  $EA(a_i)$ , and  $EO(a_i, b_i, s_k)$ ). The level of activation of a state depends on multiple other states that are directly attached toward it. Therefore, incoming activation levels from other states are combined to some aggregated input and affect the current activation level according to differential equation (11). As the combination function for each state, a continuous logistic threshold function is used: see equation (12), where  $\sigma$  is the steepness, and  $\tau$  the threshold value. When the aggregated input is negative, equation (13) is used. To achieve the desired temporal behavior of each state as a dynamical system, the difference equation represented by equation (14) is used (where  $\Delta t$  is the time step size).

$$\frac{dy_i}{dt} = \gamma_i \left[ f \left( \sigma, \tau, \sum_j \omega_{ji} y_j \right) - y_i \right] \quad (11)$$

$$f(\sigma, \tau, X) = \left( \frac{1}{1 + e^{-\sigma(X-\tau)}} - \frac{1}{1 + e^{\sigma\tau}} \right) (1 + e^{-\sigma\tau}) \quad \text{when } X > 0 \quad (12)$$

$$f(\sigma, \tau, X) = 0; \quad \text{when } X \leq 0 \quad (13)$$

$$y_i(t + \Delta t) = y_i(t) + \gamma_i \left[ f \left( \sigma, \tau, \sum_{j \in S(i)} \omega_{ji} y_j \right) - y_i(t) \right] \Delta t \quad (14)$$

In addition to this setup the mathematical energy model is integrated within the process and it triggers automatically and is represented as an internal state. Outputs of the mathematical model come from equation (10) but it is coupled with equations (1 to 9). Therefore, internally all these equations execute to represent the situation in the environment (both external and internal) to retrieve energy usage values for prepared set points. The generated energy usages values are represented in the cognitive model as sensory representation states (see Fig. 1, state



$SR(EM_i)$ ). This cognitive model assumes that the maximum strength of a state is +1 and the minimum is 0. Therefore, it is required to have a transformation to convert actual energy usage values into the scale of 0 to +1. Equation (15) is used for this requirement, where it is assumed to be that  $EM_{min}$ , and  $EM_{max}$  are minimum and maximum energy usage values provided by the mathematical model under a given situation.

$$y_{SR\_EM\_i\_T^o}(t) = 1 - \left( \frac{x_i - EM_{min}}{max - EM_{min}} \right) \quad \text{where, } max = \left( EM_{max} + \frac{EM_{max} - EM_{min}}{2} \right) \quad (15)$$

At each step (with step size  $\Delta t$ ) all the other states are updated (through equation 14) and the results of the mathematical model are used for the states  $Per(b_i, s_k)$ ,  $SD(b_i)$ , and  $CInt(b_i, s_k)$ . The effects of the mathematical model influence the behavior of these three states is explained in equations (16, 17, and 18). Let's assume that  $SR(EM_i)$  values provided by simulation of the mathematical model for night goal temperatures: 18°C, 16°C, and 14°C are  $\alpha$ ,  $\beta$ , and  $\delta$  respectively.

$$y_{SD\_T^o}(t + \Delta t) = y_{SD\_T^o}(t) + \gamma_{SD} \left[ f \left( \sigma, \tau, \omega_{29\_T^o} y_{SR\_T^o}(t) + \omega_{30\_T^o} y_{Att\_T^o}(t) + \omega_{31\_T^o} y_{CInt\_T^o}(t) + \omega_{em2\_T^o} y_{SR\_EM\_i\_T^o}(t) \right) - y_{SD\_T^o}(t) \right] \Delta t \quad \text{here if } \alpha > \beta > \delta \text{ then } \omega_{em2\_18^\circ} < \omega_{em2\_16^\circ} < \omega_{em2\_14^\circ} \quad (16)$$

$$y_{CInt\_T^o}(t + \Delta t) = y_{CInt\_T^o}(t) + \gamma_{CInt} \left[ f \left( \sigma, \tau, \omega_{32\_T^o} y_{Per\_T^o}(t) + \omega_{33\_T^o} y_{SD\_T^o}(t) + \omega_{em3\_T^o} y_{SR\_EM\_i\_T^o}(t) \right) - y_{CInt\_T^o}(t) \right] \Delta t \quad \text{here if } \alpha > \beta > \delta \text{ then } \omega_{em3\_18^\circ} < \omega_{em3\_16^\circ} < \omega_{em3\_14^\circ} \quad (17)$$

$$y_{Per\_T^o}(t + \Delta t) = y_{Per\_T^o}(t) + \gamma_{Per} \left[ f \left( \sigma, \tau, \omega_{14\_T^o} y_{SR\_T^o}(t) + \omega_{15\_T^o} y_{PD\_T^o}(t) + \omega_{16\_T^o} y_{SD\_T^o}(t) + \omega_{17\_T^o} y_{Att\_T^o}(t) + \omega_{18\_T^o} y_{Att'\_T^o}(t) + \omega_{19\_T^o} y_{PAwr'\_T^o}(t) + \omega_{20\_T^o} y_{Per'\_T^o}(t) + \omega_{em3\_T^o} y_{SR\_EM\_i\_T^o}(t) \right) - y_{Per\_T^o}(t) \right] \Delta t$$

here, if  $(\alpha - \beta \& \beta - \delta) < \theta$  (for example  $\theta = 1.0$ ) then  $(\omega_{14_{18^\circ}}, \omega_{15_{18^\circ}}, \omega_{16_{18^\circ}}, \omega_{17_{18^\circ}})$   
 $> (\omega_{14_{16^\circ}}, \omega_{15_{16^\circ}}, \omega_{16_{16^\circ}}, \omega_{17_{16^\circ}}) > (\omega_{14_{14^\circ}}, \omega_{15_{14^\circ}}, \omega_{16_{14^\circ}}, \omega_{17_{14^\circ}})$  (18)

In additionally parameter estimation is the difficult task in cognitive modeling; the parameter values used in [5] are used with very few changes (see next Section for information).

#### 4. Integrated model validation through simulations

Having identified an integrated model of combined cognitive and energy related processes it is necessary to explore its behavior for practical situations. Four scenarios are selected for simulations that cover the main aspects of the integrated model. For all the scenarios a generic setup is selected. The behavior was analyzed specifically for data available from indoor temperature 20°C at time 21:00hrs February 1, 2012 to 06:00hrs February 2, 2012 (the same data set used in [3]). It is assumed that the heating program is not using energy until the temperature reaches the night goal temperature  $T_{ng}$  (until then autonomous cooling down takes place). Once the indoor temperature becomes  $T_{ng}$  that temperature is maintained until 06:00hrs 2<sup>nd</sup> February 2012, and the indoor temperature is increased from  $T_{ng}$  to 20°C at 06:00hrs. Throughout this time interval, the outdoor temperature is assumed to be behaving as in equation (2) and  $SPF$  is calculated as in the equation (6). According to the collected data in [29] for this period of time, the minimum temperature  $T_{min}$ =-8.8°C, the temperature at sunset  $T_{sunset}$ =-2.52°C, the time of sunset  $t_{sunset}$ =17:00, and the outdoor temperature at 21:00hrs  $T_{od}$ =-6.6°C. Furthermore, for the remaining parameters the values were:  $C$ =4.6,  $\varepsilon$ =4,  $\alpha$ =0.25,  $d$ =0.1,  $T_w$ =50°C, and time step size  $\Delta t$  = 6min was for the simulation. Furthermore only 3 night goal temperatures ( $T_{ng}$ ) were selected 18°C, 16°C, and 14°C.

The first scenario explains a situation where the agent is having a strong performative desire for the higher comfort level and a less strong subjective desire to save money and energy. Therefore, this higher night goal temperature is expected to be selected. The second scenario explains a situation where the agent has a strong subjective desire to save money and energy and a less strong performative desire for comfort. Therefore the night

goal temperature with the lowest value is expected to be selected. The third scenario illustrates a situation where the agent has a wrong or biased perception. Therefore, the agent has the perception that if the energy usage is not significant for different night goal temperatures then there is no reason to select a low night goal temperature. The fourth scenario explains a situation where the agent has both a relatively high performative desire and subjective desire. This should demonstrate the compromising effect of these desires and the agent may be expected to select an average value for night goal temperature. This system is implemented as specified in Section 3.1 and implemented by using Java and provided all parameter values in XML form. The detail information about parameter values of each scenario can be found separately<sup>†</sup>.

#### 4.1. Scenario 1: Agent with a strong performative desire for higher comfort level

In this situation it is assumed to be that agent has the impression a good comfort level throughout the night period is required and it is believed that a higher night goal temperature will fulfill this. As explained in Section 3 the agent initiates the process with external stimuli and prepares for three options: 18°C, 16°C, and 14°C. For the weights of the as if body loop from  $PA(a_i)$  to  $SR(b_i)$  link only small differences are given for the different options (0.9, 0.8, and 0.7 respectively, and this is same for all the scenarios). In addition to this difference all the other parameter values of the cognitive model are identical except for the state  $PD(b_i)$ . To facilitate a strong performative desire for a higher comfort level, different weight values were used for the connection from  $SR(s_k)$  to  $PD(b_i)$ , such that  $PD(b_i)$  becomes activated stronger for higher goal temperature values. Therefore for the  $SR(s_k)$  to  $PD(b_i)$  link values 0.9, 0.6, and 0.3 are used, respectively. Fig. 2 shows the simulation results. It is very clear that having identical parameter values for all the options except for the two links, the agent has cognitively selected the highest night goal temperature. Furthermore, the results of the mathematical energy model do not directly affect performative desires states and weak values were used for  $\omega_{em1}$ ,  $\omega_{em2}$ , and  $\omega_{em3}$ . For each scenario three simulation graphs were generated and only one option is executed and only that is presented in this paper. Complete simulations results for 3 options are separately included in an external appendix<sup>‡</sup> (for all the scenarios). Therefore it is clear that the agent has developed strong activations only for the highest set point value (18°C); for the other two options no sufficient strength has developed to execute the action. Furthermore, the emerging orders of activation of the states are also very important to validate the model behavior and results are fully complied with the expected trace order in [5]. At the beginning  $PD(b_i)$  for 18°C option has shown a good strength while the same for 16°C is slightly weak and 14°C is very weak. Through this other processes have affected (specially the as if body loop) and naturally the predictive feeling of the 18°C option becomes strong and the agent executes it.

#### 4.2. Scenario 2: Agent with a strong subjective desire to save money and energy

This scenario presents effects of having a strong subjective desire to save money and energy and a less strong desire for comfort. In this situation the agent has a moderate value for performative desires and it is not too strong for 18°C option. For the connections from  $SR(s_k)$  to  $PD(b_i)$  the same value (0.6) is given for each option. Therefore, no bias is created through performative desires states. The agent uses the mathematical energy model to generate the activation level for the state  $SD(b_i)$ . From the predicted data of the mathematical energy model they may require 23.6 kWh, 22.71 kWh, 22.12 kWh for the 18°C, 16°C, and 14°C option, respectively. Therefore, this is used to decide how strong the weight value of  $\omega_{em2}$ : for the highest energy demand value 0.3, for the average energy demand value 0.5, and for the lowest 0.9 is assigned for options 18°C, 16°C, and 14°C respectively. Therefore, the agent develops a strong subjective desire for the option 14°C. In addition to this, relative to the energy demand of each option agent set the strength of the weights  $\omega_{em3}$  (for each option). Therefore, for the  $\omega_{em2}$  on 18°C get the value 0.3, 16°C get the value 0.5, and 14°C get the value 0.9. Having this configuration with identical values for other weights (for each option separately) agent has able to successfully select the set point value of 14°C. This is what is expected

<sup>†</sup> <http://www.few.vu.nl/~dte220/IEREK15ParameterData.zip>

<sup>‡</sup> <http://www.few.vu.nl/~dte220/IEREK15ExternalAppendix.docx>

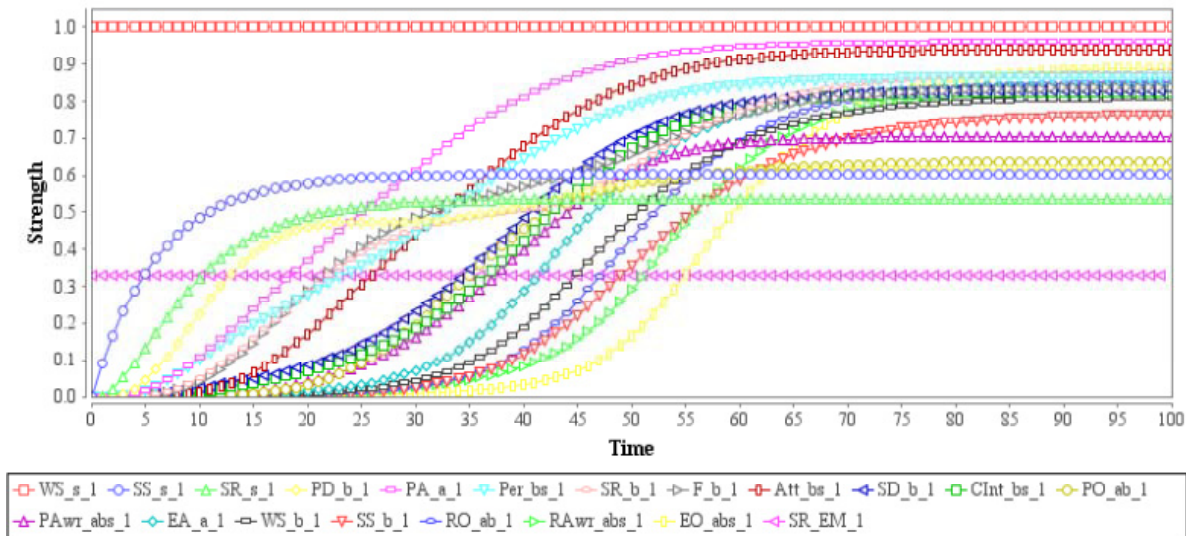


Fig. 2. Agent with a strong performative desire for higher comfort level.

and Fig. 3 provides the details particular to this option (simulation results of other two options can be found in the external appendix). Therefore, this model has successfully integrated the predictions of energy model into the cognitive model and provided realistic results. In simulation results it is clear that at the beginning the same level of  $PD(b_i)$  state has activated for 3 options and agent has developed almost the same predictive feeling value for those options. Therefore, bottom-up process passes this information to the higher cognitive levels and agent experiences attention on these three options (see external appendix). Nevertheless with the effects of  $SD(b_i)$  state only the  $CInt(b_i, s_k)$  for option 18°C has strongly developed and this has reflected through the top-down attention. This top-down attention effects on  $PA(a_i)$  on option 18°C and therefore, predictive feeling of this has increased significantly (while the top-attention of option 18°C is suppressing the other options). Therefore, agent leads to selection 18°C option and it has successfully executed (see Fig. 3).

#### 4.3. Scenario 3: Agent with a wrong or bias perception

This is a very important situation for many domains. According to Endsley's model for situation awareness [25] bias or wrong perception is considered to be as the main problem for Level 1 situation awareness and it is the cause for 76% errors in the aviation domain [26]. Here, agent is with the impression that if the energy demand for each option is not significant then there is no reason to compromise comfort level selecting a low night goal temperature. Agent prepares the process with an external stimulus and prepare for three options. In this configuration all the parameters are the same for 3 options except for predictive link in the as if body loop and for the state perception. Therefore, initially agent has developed the same strength for  $PD(b_i)$  but with the activation of  $Per(b_i, s_k)$  things have changed. Simulation results of this are presented in Fig. 4 (for all the options see the external appendix). The integrated model decides the strength of each perception state (for each option) related to the energy usage values provided by the mathematical model. The mathematical energy model calculates the energy demand for 3 options separately and that holds the values: 23.6 kWh, 22.71 kWh, 22.12 kWh for 18°C, 16°C, and 14°C. It is very clear that this difference is not very significant for each option and there is no significant energy saving by selecting a low night goal set point value. Therefore the agent develops a strong perception only for the 18°C option. This achieved by providing different weight values for  $\omega_{em1}$  for each option. The values 1.0, 0.3, and 0.2 are used for the 18°C, 16°C, and 14°C options, respectively. Due to this biased or wrong perception it positively strongly effect on  $PA(a_i)$  state on option 18°C. Having a self suppressive link on state  $PA(a_i)$  this will suppresses all its complements. Therefore As  $PA(a_i)$  for option 18°C is the strongest it suppresses all its complements and naturally strengthen the

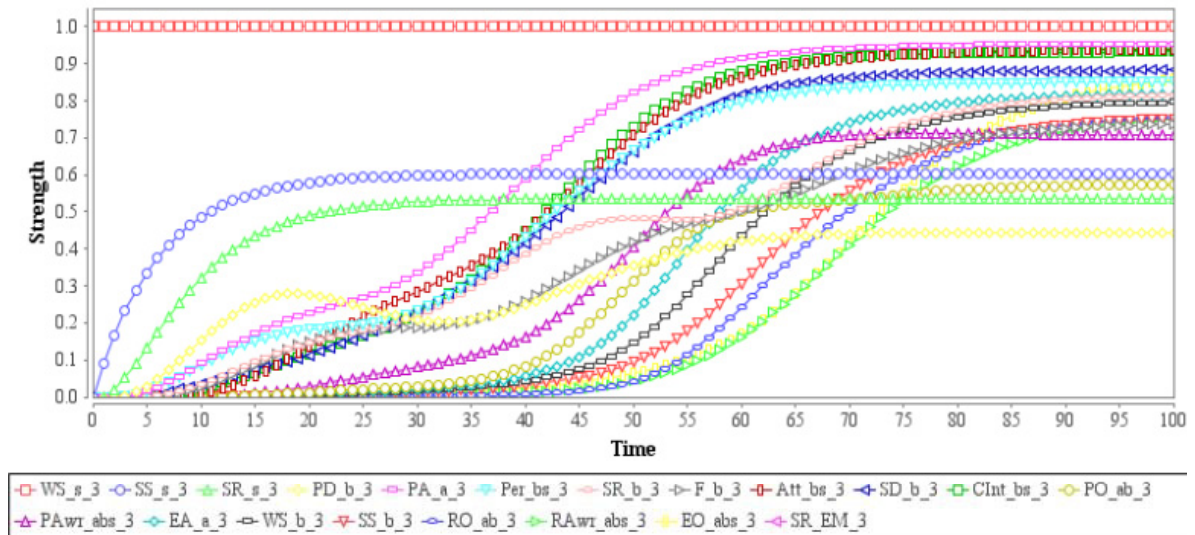


Fig. 3. Agent with a strong subjective desire to save money and energy.

feeling of predictive effect while for the other two options this is get diluted. Finally agent leads to execute to select option 18°C.

#### 4.4. Scenario 4: Agent with a strong performative desire and subjective desire

This is a special situation where agent expects both performative and subjective desires. This may seems like a conflict but in the reality this is a common situation. In such a situation it may not possible to only consider the effects of performative desire or the effects of subjective desire. Therefore combination of these two should reflect in the results and it will be a compromise of these two. According to the available three options it is expected to select 16°C options as it has sufficient comfort level and energy saving. Agent initiates the model with an external stimulus. In this situation for the predictive link in the as if body loop (i.e., from  $PA(a_i)$  to  $SR(b_i)$ ) the same values

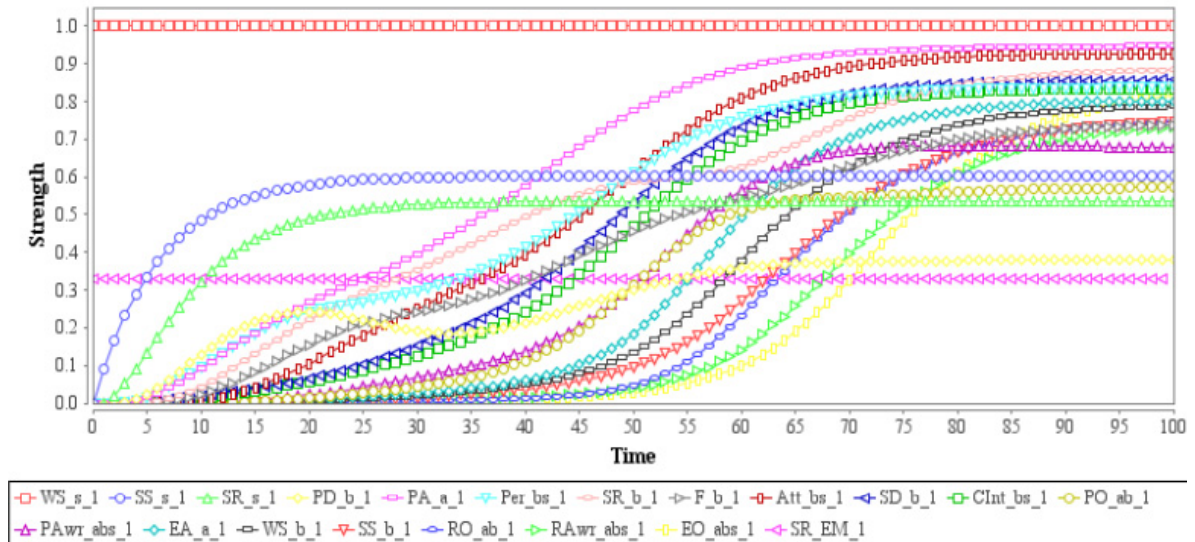


Fig. 4. Agent with a wrong or bias perception.



are used as in the scenario 1. In addition to that for the link from  $SR(s_k)$  to  $PD(b_i)$  different values are used: 0.9, 0.9, and 0.6 for options 18°C, 16°C, and 14°C respectively. Therefore it is clear that for both 18°C, 16°C the same performative desire strength can be expected. Therefore, as explained for the scenario 1 now 18°C option will not dominate the process. Similar to the other 3 simulations, for this case also the model uses the mathematical model to incorporate the expected energy usage. For the 14°C option it is smallest and therefore for the weight  $\omega_{em2}$  (for option 14°C) the value 0.8 is provided, for the 16°C option a slightly higher value (0.7) is assigned for the highest energy usage option which is 18°C a smaller value (0.3) is assigned. This also confirms that there is no strong bias through 18°C, 16°C options. In this situation by considering the energy demand values agent assigns values for the weights  $\omega_{em3}$  as 0.6, 0.9, 0.6 for three options respectively. As the state  $SD(b_i)$  is affected from  $Att(b_i, s_k)$  it has information about unconscious processes and therefore by considering the required energy demands a slight high value is given for the option 16°C while for the other two the same value is assigned. Having this configuration agent has developed strong attention on 16°C option due to the cyclic loop  $SD(b_i) \rightarrow CInt(b_i, s_k) \rightarrow Att(b_i, s_k)$ . Top-down attention effect enables and it has positively effected on action preparation of 16°C option (while it is suppressing the other two options' action preparations). Therefore, agent is experiencing a good predictive effect on this option and finally leads to execute it. Fig. 5 shows the simulation results for the option 16°C.

## 5. Discussion

Human behavior is not always easy to predict and may be complex. This is even more so if the environment in which the human functions is complex and dynamic. One example of such a complex and dynamic environment is domestic heating with the dynamics associated to indoor and outdoor air temperatures, required comfortable temperature set points over time, parameters of the heating source and system, and energy loss rate and capacity of a house. It is difficult to conduct real world experiments to analyse the dynamics and optimal efficiency of a heating system in actual daily use under all circumstances and constraints. As an alternative a simulation-based analysis may be an alternative. This paper has presented a simulation-based analysis of a domestic heating energy management system using an air to water heat pump. It has integrated an earlier developed mathematical model for this heating system's performance, and a computational dynamic cognitive model for the human's behaviour which was developed based on evidence from Cognitive Neuroscience. The model covers performative and subjective desires, perception, emotion, feeling, ownership, attention, intention, and awareness. This model has an adequate level of detail to be used as a coherent basis for various experimental needs to analyze behaviors. The presented approach

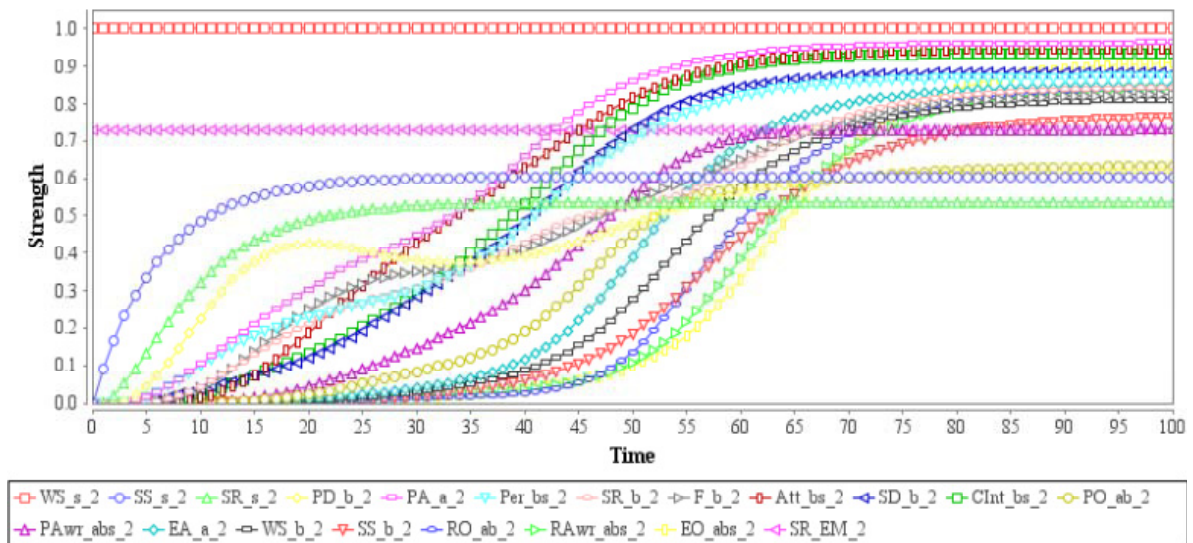


Fig. 5. Agent with a strong performative desire and subjective desire.

provides an experimental workbench in which complex scenarios can be explored by simulation experiments.

It is important to be able to examine the choices of human behavior on energy usage with a realistic setup as presented in this paper. Through this it gives an overall idea on possible impacts and allows additional information on how to motivate persons or correct their biased perceptions in a methodological approach to support lifestyle and lifestyle change in relation to energy management. This paper provides a contribution to this line of research, and may be useful as a tool for learning purposes in order to improve the awareness of humans on (heating) energy management.

## References

1. International Energy Agency. Key World Energy Statistics 2014.
2. Sanner B, Kalf R, Land A, Mutka K, Papillon P, Stryi-Hipp G, et al. 2020-2030-2050, common vision for the renewable heating and cooling sector in Europe. Luxembourg: Publications Office of the European Union, 2011; n.d.
3. Tabatabaei SA, Thilakarathne DJ, Treur J. An Analytical Model for Mathematical Analysis of Smart Daily Energy Management for Air to Water Heat Pumps. *Energy Procedia* 2014;50:589–96. doi:10.1016/j.egypro.2014.06.072.
4. Tabatabaei SA, Thilakarathne DJ, Treur J. Agent-Based Analysis of Annual Energy Usages for Domestic Heating based on a Heat Pump, Atlantis Press; 2014. doi:10.2991/ict4s-14.2014.13.
5. Thilakarathne DJ. Modelling of situation awareness with perception, attention, and prior and retrospective awareness. *Biol Inspired Cogn Archit* 2015;12:77–104. doi:10.1016/j.bica.2015.04.010.
6. Van Raaij WF, Verhallen TMM. A behavioral model of residential energy use. *J Econ Psychol* 1983;3:39–63. doi:10.1016/0167-4870(83)90057-0.
7. Wann M, Yen D, Gold HJ. Evaluation and calibration of three models for daily cycle of air temperature. *Agric For Meteorol* 1985;34:121–8. doi:10.1016/0168-1923(85)90013-9.
8. Parton WJ, Logan JA. A model for diurnal variation in soil and air temperature. *Agric Meteorol* 1981;23:205–16. doi:10.1016/0002-1571(81)90105-9.
9. Day T. Degree Days: Theory and Application. CIBSE publications; 2006.
10. Cohen IB, Schofield RE, Hall MB. Isaac Newton's papers & letters on natural philosophy and related documents. 2d ed. Cambridge, Mass: Harvard University Press; 1978.
11. Atkinson KE. An introduction to numerical analysis. 2nd ed. New York: Wiley; 1989.
12. Thilakarathne DJ. Modelling Dynamics of Cognitive Control in Action Formation with Intention, Attention, and Awareness, IEEE; 2014, p. 198–205. doi:10.1109/WI-IAT.2014.168.
13. Moore J, Haggard P. Awareness of action: Inference and prediction. *Conscious Cogn* 2008;17:136–44. doi:10.1016/j.concog.2006.12.004.
14. Engel AK, Fries P, Singer W. Dynamic predictions: Oscillations and synchrony in top-down processing. *Nat Rev Neurosci* 2001;2:704–16. doi:10.1038/35094565.
15. Haggard P. Human volition: towards a neuroscience of will. *Nat Rev Neurosci* 2008;9:934–46. doi:10.1038/nrn2497.
16. Kiefer M. Top-down modulation of unconscious “automatic” processes: A gating framework. *Adv Cogn Psychol* 2007;3:289–306.
17. Monsell S. Task switching. *Trends Cogn Sci* 2003;7:134–40. doi:10.1016/S1364-6613(03)00028-7.
18. Damasio AR. Self comes to mind: constructing the conscious brain. 1. ed. New York: Vintage Books; 2012.
19. James W. What is an Emotion? *Mind* 1884;9:188–205.
20. Lavie N. Distracted and confused?: Selective attention under load. *Trends Cogn Sci* 2005;9:75–82. doi:10.1016/j.tics.2004.12.004.
21. Aron AR. The Neural Basis of Inhibition in Cognitive Control. *The Neuroscientist* 2007;13:214–28. doi:10.1177/1073858407299288.
22. Haggard P, Clark S. Intentional action: Conscious experience and neural prediction. *Conscious Cogn* 2003;12:695–707. doi:10.1016/S1053-8100(03)00052-7.
23. Thilakarathne DJ, Treur J. Modeling intentional inhibition of actions. *Biol Inspired Cogn Archit* 2015. doi:10.1016/j.bica.2015.07.001.
24. J TD, Jan T. Modelling the Dynamics of Emotional Awareness. *Front Artif Intell Appl* 2014;885–90. doi:10.3233/978-1-61499-419-0-885.
25. Endsley MR. Situation Awareness and Human Error: Designing to Support Human Performance. *Proc. High Consequence Syst. Surety Conf.*, Albuquerque, NM: 1999.
26. Endsley MR, Garland DG. Pilot situation awareness training in general aviation. *Proc. 14th Trienn. Congr. Int. Ergon. Assoc. 44th Annu. Meet. Hum. Factors Ergon. Soc.*, Santa Monica, CA: Human Factors and Ergonomics Society; 2000, p. 357–60.
27. Thilakarathne DJ, Treur J. Computational cognitive modelling of action awareness: prior and retrospective. *Brain Inform* 2015;2:77–106. doi:10.1007/s40708-015-0013-3.
28. Treur J. An integrative dynamical systems perspective on emotions. *Biol Inspired Cogn Archit* 2013;4:27–40. doi:10.1016/j.bica.2012.07.005.
29. Treur J. On the Use of Agent-Based Simulation for Efficiency Analysis of Domestic Heating Using Photovoltaic Solar Energy Production Combined with a Heatpump. In: Oral AY, Bahsi ZB, Ozer M, editors. *Int. Congr. Energy Effic. Energy Relat. Mater. ENEFM2013*, vol. 155, Cham: Springer International Publishing; 2014, p. 143–54.